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Domain Adaptation of Binary Sensors in Smart Environments Through Activity Alignment

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ABSTRACT Activity Recognition is an active research topic focused on detecting human actions and behaviours in smart environments. In most cases, the use of data-driven models aim to relate data from sensors to an activity through a model developed by a supervised approach. In this work, we focus on the goal of domain adaptation between smart environments, which has required a novel approach to relate the concepts of domain adaptation using binary sensor and learning from daily imbalanced data. In this work, the sensor activation from a given context is translated to a different one, based on the temporal alignment from human activities. The domain adaptation of binary sensor is accomplished through a three step procedure: i) clustering of sensor activation, ii) activity based alignment of sensor data between the two environments, iii) an ensemble of classifiers used to mine a mapping function, translating sensor data between the two environments. The proposed method was evaluated over a publicly available dataset, and obtained preliminary results which were encouraging with an F1-Score of 87%.

INDEX TERMS Sensor translation, smart environments, domain adaptation.

I. INTRODUCTION

The state of the art solutions for smart environments allow for the monitoring of human activities in an increasingly less invasive way [1]. Activity Recognition (Activity Recognition (AR)) has been among the main topic of investigation in relation to the development of smart environments [2], [3]. Its application can help to improve the quality of healthcare services whilst allowing people to stay independent for as long as possible and to remain living in their own homes [4]. AR aims at developing predictive models which detect human actions and their goals [5] within a smart environment with the aim of providing assistance to the inhabitant when required. Since the earliest attempts of implementing smart environments, binary environmental sensors have been commonly proposed as suitable devices for gleaning data from the environment. The data can subsequently be used to describe daily human activities through the monitoring of the interaction of the user and the environment [6], [7].

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The technology progress witnessed in recent years has offered major advancements both in terms of hardware and software solutions. From a hardware perspective, sensing technology has become more sophisticated offering increased computational resources, increased battery life and enhanced forms of communications whilst at the same time becoming less expensive. From a software perspective, the models used to detect activities in smart environments have evolved largely taking advantage of the recent advancements in the field of machine learning. To date, supervised approaches for the development of models have arguably been the most prominent approach for AR [8]. One of the major challenges in the field of smart environments has been the ability to build effective models for the purposes of AR that are reusable across different environments [9], [10]. Nevertheless, the common denominator of models developed for the purpose of AR applications is that they are typically deeply coupled with a specific sensor deployment that generates the data used for model training. Taking this into consideration, models are not easily transferable to different environments and to different sets of activities The adaptation to a different environment requires the model to be retrained, or at least to be fine- tuned, in order to match the sensor deployment corresponding to the new environment. When using a supervised ML approach a similar transfer is seriously obstructed by the fact the training process to adapt to the new environment requires the presence of labeled data. One of the main approaches which aims to address this challenge is referred to as transfer learning, and more specifically within a method known as *domain adaptation*; a field of study which attempts to map input data between different environments [11].

In this work, this problem was addressed as a domain adaptation scenario [12] as a special case of transfer learning [13]. The goal was to predict sensor activation in a different environment with the general assumption that the same set of activities were ongoing, i.e. trying to predict the binary sensor activation in a target domain which differs from the source domain in terms of sensor deployment.

More specifically, the proposed method targets the domain adaptation of binary sensors allowing the prediction of binary sensor activations in the target environment corresponding to a specific activity, based on the activations produced in an observable source environment. One of the biggest obstacles in domain adaptation, however, is the scarcity of labeled data which relates the information between contexts to train such models. In this work, this problem is addressed by relating the sensor activation with the labeling from human activities provided in data-driven datasets.

The presence of a domain adaptation model, which is capable of transferring sensor activations from a given domain to another domain, is a highly desirable functionality, considering that location and configuration of devices across different smart environments presents an extremely heterogeneous scenario. One of the possible applications of such a method is the prediction of sensor activation for inhabitants in unseen environments [14], which in turn can be deemed useful to anticipate the user interaction in unknown environments [15] or to evaluate the differences of sensor activations between users and context. Above all, however, the domain adaptation of sensors [12] would enable multi-domain learning having the possibility of translating and reusing an available labeled set of groundtruth data, for training a model in different environments within the context of limited labelled data required for the purposes of developing supervised learning solutions.

In this work, a methodology is proposed to enable the translation of binary sensor data from labeled datasets collected in naturalistic conditions in different environments. The proposed method for domain adaptation consists of four steps:

1) Sensor activation belonging to the same activity in the source and target environment are clustered in order to detect patterns of interest to relate in the domain adaptation of binary sensors.
2) Temporal alignments of data of the domain is performed to relate the patterns of interest of an activity, and in particular the ones characterising the start and the end of a particular activity.
3) A classifier for each sensor with ad-hoc balanced dataset to predict the sensor activation in target domain is proposed. This approach enable the learning of sequence activation of target sensors from forms.
4) Fuzzy temporal windows configure the feature vector based on short and middle-term activation from the activation of sensors and activities in the input domain

The requirement for implementing the proposed method to translate sensor activations into different domains is focused on the activity labeling, whose activities are required to be included in the same contexts. Developing domain adaptation using the available labels from human activities represent an important advantage facilitating the generation of labelled datasets, whose creation normally require a time consuming manual collection and annotation process.

It should be noted that the domain adaptation by means of time alignment provides a relationship which includes uncertain and imprecision between both domains [16]. This is due to the fact that labeling is for annotating activities, however, it does not take into consideration the implicit relationship between sensor activations in contexts. The temporal alignment is a weak labeling between domains where there is not a straightforward relation between domains in all the instances.

In this way, selecting a suitable dataset for evaluation purposes can be viewed as being a convoluted task considering that such a dataset satisfy the following requirements by: i) include the same set of activities in at least two different environments, ii) include diverse development for each activities, and iii) be recorded in naturalistic conditions. In addition, the dataset should be accurately labeled. Consequently, only a limited choice of datasets could be used for the purpose of evaluation.

In addition to the problem of the lack of adequate availability of labelled data, domain adaptation also aims at addressing the intrinsic differences between various domains, considering scenarios in which the source and the target domain are heterogeneous in the sense of the set of deployed sensors and their locations [17].

In the remainder of this article, we provide further detailed descriptions of the proposed approach. Section II reviews related works and state of the art of similar approaches for domain adaptation, emphasizing the main novelties of the proposed approach. Section III presents the proposed methodology for translating the sensor information between different context domains. Section IV introduces the evaluation of the methodology analyzed in a real-world dataset. Finally, in Section V, conclusions, ongoing and future works are discussed.

II. RELATED WORKS

As previously mentioned, the deterioration of AR accuracy normally observed when moving models to new environments represents one of the biggest challenges in the domain. This deterioration phenomenon is not specifically linked to smart environments, it is more generally related to the limited generalisation abilities that ML models face in the context of all data-driven supervised applications. Training data driven AR models requires large amounts of labelled data [18]. The ability to reuse trained models in different environments with different subjects remains an open issue [19].

An AR model can be seen as a mapping function identifying a target activity y on the basis of observed sensor input X within a corresponding time interval. Considering both the input domain X and the output, *i.e.* the set of activities Y, some cases can be distinguished when moving a model M between two different contexts. In the simplest case, both the input domains X_1 and X_2 and the output domains Y_1 and Y_2 of the two environments are the same. In this case, a model exhibiting generalization issues in the new environment can be deemed as linked to overfitting *phenomena*, in most cases due to the fact of failing the assumption that the two input sets X_1 and X_2 are drawn from the same distribution [11]. However, the typical case of an AR model transfer between smart environment, the situation should be considered as being more complicated, since, different environments will correspond to different users, different sensor deployment (i.e. different input sets X), and often a different set of activities Y. The two cases of adaptation can be distinguished as *domain adaptation*, i.e. in cases where the aim is the adaptation is between X_1 and X_2, or *task adaptation* in cases in which the set of activity labels differs between the two environments [11].

In this work, the problem of *domain adaptation* and in particular the case of *heterogeneous*[1] domain adaptation was addressed. Heterogeneous domain adaptation can be performed through a means of learning a function which maps sensor data between two environments subsequently allowing a model to be trained using labelled data form a different environment.

Model adaptation, is a frequently investigated topic in AR, and has been applied for instance in egocentric AR solutions using wearable devices. In this case, the adaptation allows the model to be adapted to different users, often using personalization techniques [16], [20]. Personalization approaches allow models to be adapted to a new target subject, however, the transfer between subjects assumes that the feature space X and activity labels Y are the same between the source and the target environment. Consequently, alternative approaches have been proposed for cases requiring adaptation between the source and the target environment, either in terms of the sensor deployments or activity labels.

The current work focuses on the case of heterogeneous domain adaptation between a source X_1 and a target domain X_2 in the presence of a similar set of activities. Several studies have investigated new techniques for domain adaptation including supervised and unsupervised adaptation methods, however, the terminology used to describe these terms often varies between studies [11]. In the current study, similar to the works presented in [11], the term *unsupervised domain adaptation* is used to refer to methods attempting to perform adaptation between X_1 and X_2 where activity labels are available only for the source context Y_1, as opposed to the case of semi-supervised domain adaptation where some activity labels are available also for the target domain Y_2. A further distinction between domain adaptation techniques can be made when considering homogeneous and heterogeneous adaptation. This considers the case of domain adaptation with the same or different sensor deployment.

A recent example of adaptation between different smart environments was proposed in SLearn [18]. In this case, the authors tried to address the problem of scarcity of labelled data by enabling a shared learning approach. This approach allows models to be trained on shared training data obtained by combining annotated data which is available from multiple datasets, i.e. from multiple environments. The shared learning is accomplished through two main steps: (i) feature space remapping, and (ii) label space remapping covering both cases of domain and task adaptation. The approach aimed to implement a semi-supervised domain adaptation solution which supported shared training between different dataset with as little as 0.1% of annotated data.

In [19], authors proposed an unsupervised domain adaptation approach. The adaptation process was implemented as a three step procedure: pre-annotation of source domain, a knowledge driven based feature remapping, the generation of pseudo-labels in the target domain for model training.

In the context of transfer learning approaches, other studies have been addressing the problem of unsupervised domain adaptation methods as a weak labeling problem, e.g. in the case of audio [21] or video [22]. In the works reported in [16] a weak labeling approach to train a personalised model was presented. The approach was further developed in [23], where an automatic annotation heuristic producing weak labels was used to train personalised classifier models. The work was also detailed in [20], where an unsupervised personalization approach was proposed. The automatic annotation approach is only viable for for simple activities, whereas, for complex ADLs an automatic annotation approach is hardly achievable. The complexity is further exacerbated when using a completely unsupervised approach as in [20]. In this case the target set of simple activities was made extremely simplified, distinguishing between light, moderate and intense activities rather than trying to target complex activity labels. As an alternative, addressing the problem of scarcity of labels as a data annotation problem, has also shown its limitation, since data annotation is a time consuming and error prone process [24], [25].

Most of the proposed domain adaptation attempt to share a common phase, usually reported as *feature mapping*, whose goal is to learn a mapping function between the input feature space in the two environments, as for instance in [18], [19]. In order to provide the feature mapping from the data in the different domains, the use of unpaired data generates a more challenge, but it facilitate the application in real domains.

[1] *i.e.* in cases where the sensor deployment between the two environments is different

The unpaired data do not include information about how X_1 matches which Y_2 and it is in the topic of this work [26].

So, the domain adaptation models map between the source and target data distribution [27]. Similar approaches have been mainly developed in visual applications [28]. In the case of this work, where the goal is to predict binary sensor activations, a new approach for this problem is presented. This low-level mapping between the two domainsX_1 and X_2 requires a learning phase, in which sensor activations corresponding to the same activity label are examined in order to identify common patterns of interest corresponding to the beginning and the ending of the same activity. A similar analysis has previously been undertaken through clustering algorithms [29] providing the discovering of daily patterns which were related to tasks from users. In AR, a cluster-based ensemble method can be successfully applied as a viable option for activity recognition [30].

Moreover, domain adaptation improves the performance when including the selection of areas of interest in an unsupervised way which detail key pattern to map the data between domains the [31]. To optimize or approach, we detect areas of interest integrating a temporal alignment of key patterns extracted by clustering using the temporal progression in the activity, which provides a method to relate the unpaired data between domains in a unsupervised way. In Figure 1, we describe the relation of these key points and the approach presented in this work.

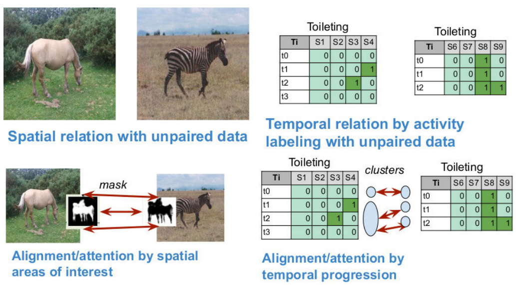

FIGURE 1. Labeling and alignment with unpaired data between domains in related stages of domain adaptation and the related of this approach.

In a similar way, sensor event prediction has also been used in the past, as in [14] where the authors explored the analysis of the input data as a time series using Recurrent Neural Networks. When including the time information in the input data, the accuracy of predicting the next sensor event was 84%. Nevertheless, in this case the prediction was limited to the scope of predicting activations within the same environment.

With respect to the state-of-the-art that has been discussed, it should be noted that, despite the presence of a significant amount of literature around this topic, the proposed methods have predominantly defined in the context of visual information, and within the sensor in smart environment they have addressed sensor event predictions rather than domain adaptation.

III. PROPOSED METHOD

In this section, the proposed domain adaptation method is presented. The method defines the development of a model which translates the activation of binary sensors between different domains or smart homes. In Section III-A, the problem being addressed is presented in a formal way as a semi-supervised heterogeneous domain adaptation case. In section III-B, a clustering method is proposed to compute relevant sensor patterns. This clustering step is also used to address the problem having of highly imbalanced number of activations of sensors for different activities. Section III-C using activity labeling presents the alignment method for relating points of time from different domains using temporal progression of activity labels. An balanced dataset for each classifier for a given target sensor is presented as an ensemble model in Section III-D. Finally, Section III-E describes the evaluation methodology of the conducted experiment based on an inverse translation and cross validation method.

A. PROBLEM DESCRIPTION

Considering a given smart environment A, let $S^A = \{S_1^A, \ldots, S_{|S^A|}^A\}$ be the set of sensors deployed in the environment, and let $L^A = \{L_1^A, \ldots, L_{|L^A|}^C\}$ be the set of activity labels which have been observed and annotated in A. The process of AR can be seen in this context as a labeling problem, creating a function that links a set of sensor activations S_i^A to the corresponding set of conducted activities L_i^A, i.e. a labeling function $S_A \rightarrow L_A$.

Both the binary sensor activations and activities are described by a set of temporal instances within a given interval of time, defined by a starting and ending point as presented by Eq. (1):

$$\begin{aligned} S_i^A &= \{S_{i_0}^A, \ldots, S_{|S_i|}^A\}, \quad S_{ij}^A = \{S_{i_{j0}}^A, S_{i_{j+}}^A\} \\ L_i^A &= \{L_{i_0}^A, \ldots, L_{|L_i|}^A\}, \quad L_{ij}^A = \{L_{i_{j0}}^A, L_{i_{j+}}^A\} \end{aligned} \tag{1}$$

where: i) $|S_i^A|$ represents the number of temporal intervals for a given binary sensor, ii) $|L_i^A|$ represents the number of temporal intervals for a given daily set of activities A_i, and iii) $S_{i_{j0}}$,$S_{i_{j+}}$ the starting and ending point of a time interval for the sensor S_i^A, respectively.

It should be noted that the cardinality of L_i^A and S_i^A can vary significantly between long and short activities (e.g. preparing a meal vs leaving the house) and activities that generate a high number of activations (e.g. cooking) whereas other are intrinsically less verbose activities (e.g. leaving house) can be expected to generate relatively few sensor activations. In this work, we provide a domain adaptation between two sensor contexts A, B by means of activities L^A, L^B which translates the binary activation of sensors S^A to S^B. The translation model M provides the sensor representation $M(A \rightarrow B)$ from the sensor activation in the context S_A to the sensor activation in the context S_B in case of developing the activities L^A.

$$M : \{S_A, L_A\} \rightarrow \{S_{A\rightarrow B}, L_A\} \tag{2}$$

Figure 2 illustrates an example of sensor to sensor translation (also know as domain adaptation) from two different context domains A and B, by means of a translation model.

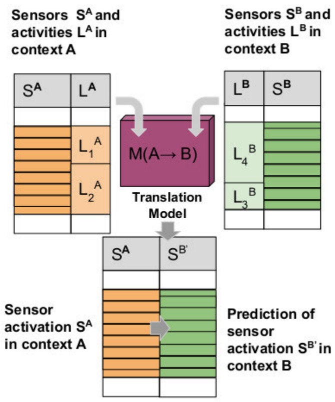

FIGURE 2. **From sensors S^A, S^B and activities L^A, L^B in contexts A and B respectively, a translation model learn the activation of sensors in domain S^B from the activation of sensors S^A.**

The following Sections describe the stages defined for developing a domain adaptation model translating binary sensor activation between the domains A and B.

B. SELECTION OF FREQUENT KEY PATTERNS IN ACTIVITIES BY MEANS OF FUZZY CLUSTERING

A dataset is considered to be imbalanced when its classes are not equally represented [32]. In the scenario of considering activities of daily living, the datasets suffer from a severe class imbalance problem in activities and sensor activation [6], [7], [33]. Within the application context targeted in this work, an extreme imbalanced relation between activation and non-activation in the sensor can be expected due to the activities that are intrinsically more verbose in the sense of the number of activations they generate and activities that generate a sparse set of activations. In Figure 2, the activation percentages of time-slots for each binary sensor is detailed, providing a visual example of this type of imbalance [6]. Learning the activation of these infrequent sensors in the daily timeline is a needle-in-a-haystack problem.

In order to address this type of imbalance, our implementation proposes a selection method of relevant sensor patterns within the daily activities where sensor data are automatically aggregated into clusters to improve on recognition accuracy with respect to classification models [34] while at the same time being robust to imbalanced and uncertain conditions with noisy data [35]. The proposed method is based on fuzzy clustering using the Fuzzy C-means algorithm [36] which is a centroid-based method used to compute the clusters and membership degrees between 0 and 1 for each sample to the cluster centers. These clustering approaches with the integration of fuzzy approaches, specifically the fuzzy C-means algorithm [36] have provided suitable methods to extract meaningful patterns from sensors [37]. The selection of the fuzzy C-means is based on the sturdiness in handling noisy data samples [38] and the ability to express ambiguity in relating instances to several clusters, being robust in terms of local minima of the objective function [39]. Despite the fact that the use of fuzzy C-means can be affected by a high dimensional data set, the dimension size is defined by the number of binary sensors, whose value is limited (between ten and one hundred in the dataset evaluated in this work [6]). Fuzzy C-means and other clustering approaches have been successfully used in AR to detect key patterns [40], [41].

First, we initially segment the timeline in time-slots using the window size $\Delta t = 60s$ based on the standard reference from [6], [42], [43]. Second, we divide the timeline $T = \{min(S^0_{i_j}), max(S^+_{i_j})\}$, which configures the range of time between first starting point $min(S^0_{i_j})$ and the ending point $max(S^+_{i_j})$. The range of evaluation for each time-slot is defined by a sliding window between $[t_i, t_i + \Delta t]$. For each time-slot and a given sensor, we determine its activation based on whether it has been activated (even just partially) within it:

$$S(t_i, s) = \begin{cases} 1 & \exists [S^0_{s_j}, S^+_{s_j}] \cap [t_i, t_i + \Delta t] \forall S_{s_j} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Thirdly, a fuzzy clustering technique is applied to compute the relevant patterns of time-slots for each activity. The purpose of computing clusters of time-slots for each activity is to obtain key patterns which are independent of their frequency of appearance in the timeline. In this manner, the selection method based on clustering prevents the possibility that some relevant key patterns could result in begin undetected due to their low frequency. For example, in the activity leaving home, the opening or closing the door is developed in one single time-slot, even if the empty home situation, with none of the sensors being activated for a long time involves a large number of time-slots. The proposed clustering method is able to compute the two clusters (opening/closing door and inactivity) as a relevant and neutral representation of the activity leaving home with independence of their frequency of these patterns

Forthly, it is necessary to remove noisy clusters which result due to spurious instances of an activity. For that, the relative frequency of clusters of the same activity are counted to evaluate the relevance of them while the full time-line. We call $f_{C_i^L}$ as the relative frequency of the cluster C_i of the activity L_j which is computed as $f_{C_i^L} = \sum C_i^{L_j} / \sum_j C_j^L$, where $\sum_j C_j^L$ represents all temporal instances of the activity L_j and $\sum C_i^{L_j}$ represents the instances of the cluster. So, the relative frequency of the cluster in all instances of the activity is used as metric which can be thresholded $f_{C_i^L} < \beta$ rejecting the infrequent clusters to maintain only these relevant clusters which better describe the activity in most of the activity occurrences.

Finally, we note as result of this step, both the center and the number of clusters for each activity provide an interpretable representation from sensors and human behaviours, in addition to, a metric of the complexity of the activities developed in different domains and contexts. Figure 1 provides a visual representation of the clustering method presented in two different environments, based on a real dataset. From the clusters obtained, we note: i) the relation between activities and sensor activation described by clusters provides an interpretable representation of the user activity and sensor interaction, ii) the differences in developing same activities between the inhabitants and domains in the context A and B in terms of number of sensors and activation describe the difference between domains.

C. ALIGNMENT BETWEEN TIME-SLOTS USING ACTIVITY LABELING

One of the main challenges in the domain adaptation process consists of aligning the source and the target data which is necessary to learn the translation model between the two environments. The reason behind the complexities of relating two scenes is that it is impossible to replicate the same activities maintaining the order and duration between domains in a naturalistic manner. Furthermore, replicating activities in the same order to other inhabitants/contexts avoids the natural characteristic of spontaneity of the inhabitant when developing human activities. Observing human activities in smart environments requires intrinsic naturalistic conditions when collecting inhabitant behaviour. In our approach for translating sensor activation between different contexts, we need to relate the occurrence of a time-slot from the source domain to another time-slot from the target domain.

In order to align the time-slots of the sensor activation between the two domains the activity labeling and clusters obtained in the previous step are used. First, for each cluster C, a number of representative time-slots are selected, as random time-slots from the timeline whose membership degree to the cluster overcomes a threshold $d_C > \alpha$. Then, the progression w_A of the time-slot t_A within the activity L^A as a value between [0, 1] is computed as $w_A = (t_A - L_0^A)/(L_+^A - L_0^A)$, where $[L_0, L_+]$ are the starting and ending points of time for the activation of the activity. In a straightforward way, a selection of a time-slot t_B for the same activity in the other context L^B with a similar temporal progression $w_B \simeq w_A = |w_B - w_A| < \sigma$, where σ defines the similitude margin of progression, in the other context provides a relation between both time-slots and domains $t_A \rightarrow t_B$. In Algorithm 1, we describe the alignment of time-slots between contexts with a similar temporal progression between same activities.

Balancing the dataset was proven to enhance performance in dealing the activation/non activation within the same and other activities with an ad-hoc learning for each classifier of the ensemble [7]. In order to select the time-slots which compose the dataset for learning the activation of the sensor S_j, an ad-hoc balanced dataset was generated for each

TABLE 1. **Relevant clusters obtained for activities: Snack, Toileting, Breakfast, Showering and Lunch in two Houses A, B for different inhabitants and sensors [6].** ***Rf*** **defines the relative frequency of the activity pattern.**

House A

Activ	Rf	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Snack	1.0	0	0	0	0	0	0		0	1	0	1	0
Snack	0.14	0	0	0	1	0	0		0	1	0	1	0
Snack	0.14	0	0	1	0	0	0		1	1	0	0	0
Snack	0.14	0	0	0	0	0	0	0	0	0	0	0	0
Snack	0.14	0	0	0	0	0	0	0	1	1	0	0	0
Toileting	0.86	0	0	0	0	0	0	0	0	0	0	0	0
Toileting	0.24	0	0	0	1	0	0	0	0	0	1	0	0
Toileting	1.0	0	0	0	1	0	0	0	0	0	0	0	0
Toileting	0.4	1	0	0	1	0	0	0	0	0	0	0	0
Toileting	0.14	0	0	0	0	0	0	0	0	0	1	0	0
Toileting	0.2	1	0	0	1	0	0	0	0	0	1	0	0
Showering	1.0	0	0	0	0	0	1	0	0	0	0	0	0
Showering	0.1	1	0	0	0	0	1	0	0	0	0	0	0
Breakfast	0.27	0	0	0	0	0	0	0	0	0	0	0	1
Breakfast	1.0	0	0	0	0	0	0	0	0	0	0	0	0
Breakfast	0.55	0	0	0	0	0	0	0	0	0	0	1	1
Breakfast	0.1	1	0	0	0	0	0	0	1	1	0	0	1
Breakfast	0.27	0	0	0	0	0	0	0	0	1	0	0	0
Breakfast	0.1	1	0	0	0	0	0	0	1	0	0	1	1
Breakfast	0.18	0	0	0	0	0	0	0	0	0	0	1	0
Breakfast	0.1	1	0	0	0	0	0	0	1	1	0	0	0

House B

Activ	Rf	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Snack	1.0	0	0	0	0	0	0	0	0	0	0	0	0
Snack	0.78	0	0	0	0	0	0	0	0	0	0	0	1
Snack	0.3	1	0	0	0	0	0	0	1	0	0	0	1
Snack	0.6	1	0	0	0	0	0	0	0	0	0	0	1
Snack	0.39	0	0	0	0	0	0		1	0	0	0	0
Snack	0.26	0	0	0	0	0	0	0	0	0	1	0	1
Snack	0.30	0	0	0	0	0	0	0	1	0	0	0	1
Snack	0.1	1	0	0	0	0	0	0	0	0	0	0	1
Toileting	1.0	0	0	0	1	0	0	0	0	0	0	0	0
Toileting	0.27	0	1	0	1	0	0	0	0	0	0	0	0
Toileting	0.2	1	0	0	1	0	0	0	0	0	0	0	0
Toileting	0.16	0	0	0	1	0	0	0	0	0	0	0	0
Showering	1.0	0	0	0	0	1	0	0	0	0	0	0	0
Breakfast	0.64	0	0	0	0	0	0		1	0	0	0	0
Breakfast	0.29	0	0	0	0	0	0	0	0	0	0	1	0
Breakfast	1.0	0	0	0	0	0	0	0	0	0	0	0	0
Breakfast	0.14	0	0	0	0	0	0		1	0	0	1	0
Breakfast	0.50	0	0	0	0	0	0		0	0	0	0	1
Breakfast	0.2	1	0	0	0	0	0	0	0	0	0	0	1
Breakfast	0.14	0	0	0	0	0	0	0	1	0	0	0	1

Id	Sensor A	Sensor B
S1	Bathroom PIR Basin	Living PIR Door
S2	Kitchen PIR Cooktop	Bathroom PIR Basin
S3	Entrance Magnetic Maindoor	Entrance Magnetic
S4	Bathroom Flush Toilet	Bathroom Flush Toilet
S5	Bathroom Magnetic Cabinet	Bathroom PIR Shower
S6	Bathroom PIR Shower	Bedroom PIR Door
S7	Bedroom Pressure Bed	Bedroom Pressure Bed
S8	Kitchen Magnetic Fridge	Kitchen Magnetic Fridge
S9	Kitchen Magnetic Cupboard	Living Pressure Seat
S10	Living Pressure Seat	Kitchen Magnetic Cupboard
S11	Kitchen Electric Microwave	Kitchen Electric Microwave
S12	Kitchen Electric Toaster	Kitchen PIR Door

Algorithm 1 Alignment of Time-Slots Between Contexts With a Similar Temporal Progression Between the Same Activities

```
Data: t_A, L^A = [L^A_0, L^A_+]
Result: t_B
/* Alignment random method t_A, t_B                    */
w_A = (t_A − L^A_0)/(L^A_+ − L^A_0);
// For same activity in the B context
for L^B ∈ B do
    // Obtain a random time-slot in B
    t_B = randomTimeSlot(L^B);
    w_B = (t_B − L^B_0)/(L^B_+ − L^B_0);
    // Have they a similar activity
       progression?
    if |w_B − w_A| < σ then
        return t_B;
    else
        _
```

Algorithm 2 Method for Selecting the Ad-Hoc Dataset for the Sensor S_j

```
Data: S_j, {C^L_1, ..., C^{|L|}_| C|}, N
Result: {t_A ←→ t_B}
/* Ad hoc dataset for learning target
   sensor S_j                                      */
dataset ← {};
// i) To select clusters C^L_j where
   sensor S_j is presented
for C^L_j ← C^L_j(S_j) > α do
    Δ|dataset| = 0;
    // To select N_i samples
    while Δ|dataset| < N_i = N × C^{L_j}_i do
        // To select a time-slot from
           cluster
        t_B ← μ(t_B, C^L_j) > α;
        Δ|dataset| + +;
        dataset = dataset ⋃ t_B;
        // ii) To select a random
           time-slot from non-activation
           clusters of sensor S_j of same
           activity L
        if ∃ \overline{t_B}, C^L_k μ(\overline{t_B}, C_K) < 1 − α then
            dataset = dataset ⋃ \overline{t_B};
        else
            _
// iii) To select a random time-slot
   from idle activities of sensor S_j
for C^L_j ← C^L_j(S_j) < 1 − α do
    Δ|dataset| = 0;
    // To select N_i samples
    while Δ|dataset| < N_i = N × C^{L_j}_i do
        // To select a time-slot from
           cluster
        t_B ← μ(t_B, C^L_j) > α;
        dataset = dataset ⋃ \overline{t_B};
        Δ|dataset| + +;
return dataset;
```

classifier trained for this given target sensor. The ad-hoc balancing process combines time-slots between activation and not activation, as the integration of three cases, aiming at improving the ability to discriminate the activation in the learning of the target sensor: i) time-slots where the target sensor is activated in a cluster of a given activity, ii) time-slots where the target sensor is not activated in other clusters of the same activity (if it exists), and iii) time-slots from idle activities where the target sensor is not activated for any of its clusters. We note, with this proposed method the relation between samples with activation and non activation for each sensor is weighted in a relation between [1/2, 1/3] depending on the activation distribution of the sensor within the patterns recognized for each activity in point ii). The number of time-slots for activity and idle activation are defined as $N_A, \overline{N_A}$.

For generating pairs of time-slots $t_A \longleftrightarrow t_B$, which configure the ad-hoc balanced dataset for each sensor S_j, we adhere to the following stages. As we detailed previously, we select clusters where the sensor S_j presents a representative activation, and other clusters where it is not activated. The selection of a relevant cluster is computed by a threshold degree α which evaluates of the membership degree of the time-slot $\mu(t_B, C^L_j)$ in a given cluster C. Once we select a relevant clusters C^L_j, we collect a number of time-slots for each cluster which is limited according to the relative frequency of the cluster $N_i = N\dot{C}^{L_j}_i$ in the dataset. Finally, the random selection of time-slots which pertain to the cluster is developed by: i) selecting time-slots whose membership degree overcomes $\mu(t_B, C^L_j) > \alpha$; analogously for non activation, ii) and iii) selecting random time-slots whose membership degree is lower than $\mu(t_B, C^L_j) < 1 - \alpha$. The stochastic method for generating pairs of time-slots in a balanced dataset is described in Algorithm 2.

D. LEARNING FROM A BALANCED DATASET FOR SENSOR TO SENSOR TRANSLATION

The problem of translating the binary sensor activation from an input context to a target context is formalised as a sequence to sequence problem. In this work, we propose developing the learning using an ensemble of classifiers with an ad-hoc balanced dataset aiming to enhance the performance for data from binary sensors [7].

Once the training process has been completed, each target classifier can be presented with input data from the binary sensor activation from the input context in order to predict the activation or non-activation of the target sensor in the target domain. As features from the binary sensor from the input context, multiple temporal windows [7] were used for segmentation, and more specifically, incremental fuzzy temporal windows (FTWs) which were proven to provide a suitable representation of the activation of binary sensors for the purposes of learning [7], [44]. The representation of binary sensors with Fuzzy Temporal Window by Trapezoidal Membership Functions is defined in Appendix. In order to simplify the creation of the incremental fuzzy temporal windows, the Fibonnaci series was used [45], where a set of incrementally ordered evaluation times $L = \{L_1, \ldots, L_{|L|}\}, L_{i-1} < L_i$ defines the limits of the trapezoidal functions for several FTWs according to the temporal window index $T_k = T_k(\Delta t_i)[L_k, L_{k-1}, L_{k-2}, L_{k-3}]$ from the elapsed time Δt_i to time-slot t_i. Moreover, temporal activation of binary from preceding FTW L_- is combined with oncoming FTWs L_+ to increase the learning performance [46]. Figure 3 illustrates the configuration of fuzzy temporal windows evaluated in this work which represents the short-term activation of binary sensors defined by the Fibonacci sequence.

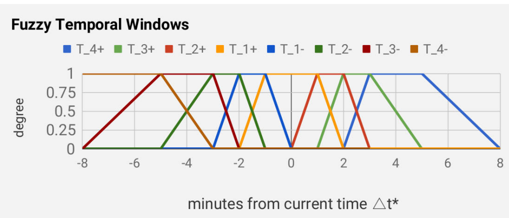

FIGURE 3. **Example of preceding FTWs $L_- = \{0, 1, 1, 2, 3, 5, 8\}$ and oncoming FTWs $L_+ = \{0, 1, 1, 2, 3, 5, 8\}$, which are defined by the Fibonacci sequence in a timeline.**

At the end of this stage, the ensemble of classifiers is able to predict the translation for each time-slot from the input sensor context to the target sensor context, by means of training using a balanced dataset for each classifier and a fuzzy temporal representation of input binary sensors.

E. EVALUATION METHOD BASED ON CROSS VALIDATION AND INVERSE TRANSLATION

As previously mentioned, the binary sensor activation and developed activities cannot be expected to be generated with the same conditions and behaviours be- tween domains/inhabitants. Therefore, the method aims at learning the translation of sensor activations from the input domain to the target domain using a limited amount of data.

We cannot therefore rely on the presence of groundtruth data in the target domain. As such, a different evaluation experiment is proposed to examine the validity of the approach. Assuming that groundtruth data is available in large quantities, only for the source domain, the translation process between domains is repeated to learn the mapping function in the opposite direction $B \rightarrow A'$. This method allows verification of the quality of a sensor event prediction in a different environment by comparing the original sensor activations in the source domain, after they have been translated into the target domain and back to the source domain following the same process.

First, a cross-validation segmentation is applied in both datasets, where the data are split into training and test in a rotating process which subsequently involves the evaluation of the full dataset. As a cross-validation method for the human activity dataset and binary sensors, one-day-left cross-validation is suggested and applied in this approach [6], [7], [42]. Second, we learn and evaluate the translation model $input \rightarrow target'$ for each training partitioning sample from the cross-validation obtaining the prediction for each day of the dataset. At the end of cross- validation, the challenge is the joining of all days from the evaluation to compose a predicted timeline with the activities from the input domain, however, including the sensor activation of the target domain.

Thirdly, the predicted timeline in target domain is used to replicate the process to compute the translation model $target' \rightarrow input'$ to a predicted sensor activation in the input domain. Exactly the same learning and evaluation with leave-one-day-out cross- validation is replicated. At least, the combination of the sensor activation for each of the evaluation days generates a prediction of the input sensors. Evaluation metrics based on classification (precision, recall, f1-score) between the prediction sensor activation and the ground truth sensor activation in the input domain are used to describe the performance of the translation model.

It should be noted that this evaluation method is particularly strict in this case, due to the fact that the error in sensor to sensor translation is calculated following a double translation process. First, the model error $\delta_{input \rightarrow target}$ is incorporated in the input data of the target model generating noisy data; and second, the model error $\delta_{target \rightarrow input}$ in the inverse translation is also accumulated into the final results of sensor to sensor translation.

As summary, in Figure 4, we illustrate the evaluation method described in this section, where we show the segmentation of one-day-left cross-validation of data which are trained to build the domain adaptation from source A to target B. Symmetrically, the process is repeated from domain B to domain A', which enables comparing the ground truth of A with A'.

IV. EVALUATION EXPERIMENT

In this Section, we present an evaluation of the methodology for translating sensors between different domains which are aligned by human activity labels. As described in the Introduction Section, selecting a suitable dataset for evaluation purposes is a convoluted task due to the requirements of including the same activities in different domains by different contexts/inhabitants and including several days of data collection in naturalistic conditions. Based on these requirements, we evaluated the dataset Ordoñez [6]. In this dataset, two experiments were carried out in two different houses (A and B). In house A with 4 rooms, 12 binary sensors describe 14 days where 9 daily activities were carried out over a period of 19,932 minutes. In house B with 5 rooms,

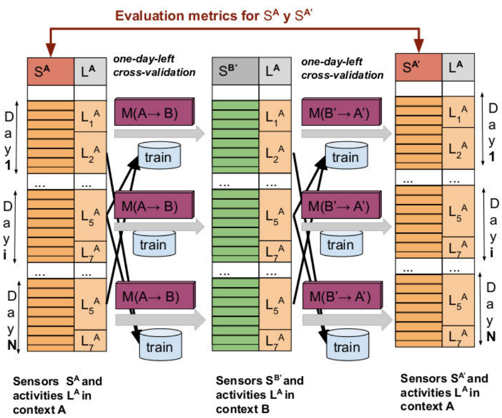

FIGURE 4. Evaluation based on an inverse translation and cross validation method. First, we translate sensor activation from input to target. A second translation process with the target prediction enables comparing the ground truth of the prediction in the input domain.

a further 12 binary sensors describe 22 days where 10 daily activities are carried out over a period of 30,495 minutes. A map of the houses together with the senor deployment is shown in Figure 5. In addition, the inhabitants and behaviours between A and B context differ (each one corresponding to a different user), as well as in the labeling (data were labelled manually by the inhabitant). The difficulties in domain adaptation in this problem are notable, for example, we note: i) the differences in the nature of sensors: bathroom cabinet, bedroom pir door, living pir door, electric toaster and kitchen pir door, and ii) the location is different in the maps, i.e. the lack of sensor in one of the living rooms in house B regarding house A so that the sensor *Living-Pressure-Seat* is completely different between domains. This type of differences between House A and House B provided the typical differences in AR in real-time environments [7].

FIGURE 5. Map of houses A and B together with its sensor deployment.

Two modifications have been made to the original dataset: i) we fix same duration (14 days) in context B to provide same balance and size of data in learning the translation model, ii) the *dinner* activity in House B was changed to *snack* to provide exactly same activities between House A and B, which are: snack, toileting, lunch, breakfast, sleep, leaving, grooming, showering, spare time/tv. We note, the deployed sensors between houses A and B have got a different location and nature in the rooms to describe the daily activities of the inhabitants (see Table 2).

TABLE 2. Description of sensors in the two contexts of houses A and B. In last column (% Activation), percentage of time-slots when the sensor is activated.

House A				House B			
room	type	type	act	room	type	type	act
Bathroom	PIR	Basin	1.06%	Bathroom	PIR	Basin	1.40%
Bathroom	Flush	Toilet	0.31%	Bathroom	Flush	Toilet	0.61%
Bathroom	Magnetic	Cabinet	0.09%	Bathroom	PIR	Shower	0.27%
Bathroom	PIR	Shower	0.53%	Bedroom	Pressure	Bed	33.33%
Bedroom	Pressure	Bed	39.33%	Bedroom	PIR	Door	1.01%
Entrance	Magnetic	Maindoor	0.17%	Entrance	Magnetic	Maindoor	0.29%
Living	Pressure	Seat	44.32%	Living	PIR	Door	2.94%
Kitchen	Electric	Microwave	0.49%	Living	Pressure	Seat	25.2%
Kitchen	Electric	Toaster	0.29%	Kitchen	Magnetic	Fridge	0.37%
Kitchen	PIR	Cooktop	0.92%	Kitchen	Magnetic	Cupboard	0.09%
Kitchen	Magnetic	Fridge	0.40%	Kitchen	Electric	Microwave	0.27%
Kitchen	Magnetic	Cupboard	0.22%	Kitchen	PIR	Door	1.52%

As mentioned in section III-E, where the evaluation method is described, the context of houses A and B have been segmented applying a one-day- left cross-validation in both datasets according to the stages described in following Sections. The code and data are available in the open repository for the community and evaluation purposes https://github.com/AmsterdamVibes/transfer-sensor.

A. EXPERIMENTAL SETUP

In this Section, the proposed methodology from Section III has been implemented to evaluate the Ordoñez dataset. First, segmentation and clustering of frequent key patterns are detailed. Second, implementation of alignment between time-slots with a balanced datasets is described. Third, FTWs configuration and selected classifiers are identified. The key parameters in experimental setup are described in Table 3 to clarify the parametrization of the work.

1) SEGMENTATION AND CLUSTERING OF FREQUENT KEY PATTERNS

First, the binary sensor and activity activation were segmented in time-slots of window size $\Delta t = 60s$ [6], [42]. Based on the time-slots of this segmentation, we compute the relevant patterns of sensors of activity in the timeline using Fuzzy C-means. Next, we remove those non-relevant clusters of relative frequency below $\beta = 0.1 < f_{C_i^L}$.

The number of clusters obtained for each activity and contexts A and B are presented in Table 4. In Figure 1, we show relevant clusters obtained for activities: Snack, Toileting, Breakfast, Showering and Lunch in Houses A and B.

2) SETTING THE ALIGNMENT BETWEEN TIME-SLOTS WITH A BALANCED DATASETS

As previously mentioned, an ensemble of classifiers is proposed in our method, where for each sensor of the target context a classifier receives as input the binary sensor activation from the input context in order to predict the activation or non-activation of the target sensor in the other domain.

TABLE 3. Key parameters in experimental setup.

Param	Value	Description
$\beta < f_{C_i^L}$	$\beta = 0.1$	β is a threshold to remove non-relevant clusters using relative frequency $f_{C_i^L}$
$d_C > \alpha$	$\alpha = 0.75$	α is the threshold degree to determine if a sensor is activated in a cluster
$d_C < 1-\alpha$	$\alpha = 0.75$	α is the threshold degree to determine if a sensor is not activated in a cluster
N_A	$N_A = 400$	N_A is the maximal number of time-slots selected in the dataset for each cluster
L_-	$L_- = \{1,2,3,5,8\}$	L_- defines the limits of short-term FTWs for preceding temporal features
L_+	$L_+ = \{1,2,3,5,8\}$	L_+ defines the limits of short-term FTWs for ongoing temporal features
L_-	$L_- = \{1,2,\ldots,610\}$	L_- defines the limits of long-term FTWs for preceding temporal features
L_+	$L_+ = \{1,2,\ldots,233\}$	L_+ defines the limits of long-term FTWs for ongoing temporal features
W	$W = \{5,15\}$	W temporal margin of confidence from ground truth and prediction.

TABLE 4. Number of clusters obtained for each activity and contexts A y B.

	N clusters	
Activity	**House A**	**House B**
Snack	5	7
Toileting	6	4
Showering	2	1
Breakfast	8	8
Lunch	13	18
Grooming	4	5
Leaving	2	4
Spare Time	4	5
Sleeping	1	4
Total	45	56

As already introduced in algorithm 2, for each target sensor to learn from the target domain, an ad-hoc balanced dataset is calculated for its classifier including:

- i) time-slots where the target sensor is activated in a cluster of a given activity selecting the time-slots whose membership degree of the sensor overcomes $d_C > \alpha$.
- ii) time-slots for the same activities of case i) where sensor is not activated (if exists) selecting those whose membership degree is lower than $d_C < 1 - \alpha$.
- iii) time-slots from idle activities where the target sensor is not activated for any of its cluster selecting those whose membership degree is lower than $d_C < 1 - \alpha$

The threshold to the evaluate the degree was set to $alpha = 0.75$, and the maximal number of time-slots as $N_A = 400$.

Following this step, the time-slots $t_A \longleftrightarrow t_B$ which are aligned by a similar temporal progression w for the same activity in both contexts $w_B \simeq w_A$ are identified according to the Algorithm 1.

3) FUZZY TEMPORAL WINDOWS AS FEATURES OF AN ENSEMBLE CLASSIFIER

In order to build a feature vector with the temporal activation of binary sensors from the input domain, we compute the preceding FTW L_- and oncoming FTW L_+ [46] for each time-slot, which was proven to provide a suitable representation of the activation of binary sensors for learning purposes [7], [44]. The definition of FTWs has been developed using the Fibonacci sequence [45], [47]. Two models of FTWs have been evaluated: i) short-term FTW $L_- = L_+ = \{1, 2, 3, 5, 8\}$, which represents the binary sensor previous and ongoing 8 minutes close to real-time translation, ii) long-term FTW $L_- = \{1, 2, 3, 5, \ldots, 610\}, L_+ = \{1, 2, 3, 5, \ldots, 233\}$, which represents the binary sensor activation from previous 10 hours and the current ongoing 4 hours.

The FTW are computed under a sliding window approach from a given current time (refer to Figure 3). The temporal features describe the feature vector for each time-slot from which the classifier relate the temporal activation from input domain to predict the activation in target domain by the ensemble of classifier.

Finally, several classifiers for learning sensor to sensor translation in the ensemble of classifiers have been evaluated. In the case of traditional models, we selected: Random Forest (RF) and Support Vector Machine (SVM). In addition, we have included Deep Learning models for predicting the activation of sensors: Convolutional Neural Networks (CNN) and Long short-term memory (LSTM), which have been previously proposed in domain adaptation for other contexts [48], [49].

B. RESULTS

This section presents the results of the evaluation experiment using two different configurations of FTWs (short and long term features) and several set of classifiers (SVM,RF,CNN and LSTM).

Due to the severe imbalance problem of sensor activation in the timeline, simple accuracy may be biased and therefore not considered as a suitable metric. For this reason, the metrics of precision $\frac{TP}{TP+FP}$, recall $\frac{TP}{TP+FN}$ and F1-score $\frac{2 \times P \times R}{P+R}$ based on the activation of sensor from ground truth and prediction [7] within a temporal margin of confidence W were used for evaluation. The temporal margin of confidence W checks that the activation of the prediction is within a number of time-slots of the ground truth. This is key in the sensor to sensor translation metrics because of the delays in labeling, prediction and variations in the behaviour of the inhabitants under naturalistic conditions while developing the activities. In the experiment, the margin of confidence was set to $W = 5$, within 5 minutes or time-slots, and we have evaluated the variance of the metric F1-score $\Delta F1$ with a wider temporal margin $W = 15$.

Tables 5 and 6 report the results of sensor to sensor translation for SVM and RF, respectively for each sensor from the input domain regarding the evaluation method proposed in the methodology. In addition, Tables 7 and 8 report the results of sensor to sensor translation for CNN (4 layers with 24 kernels) and LSTM (2 layers with 100 units), respectively.

TABLE 5. Precision P_5, recall R_5 and F1-score F_5 in sensor to sensor translation for SVM with a temporal margin of confidence $W = 5$. F_{15} represents the F1-score with $W = 15$.

Sensor	long term FTW				short term FTW			
	P_5	R_5	F_5	F_{15}	P_5	R_5	F_5	F_{15}
BathroomPIRBasin	0.11	0.86	0.20	0.34	0.44	0.99	0.61	0.69
KitchenPIRCooktop	0.31	0.90	0.46	0.55	0.45	0.99	0.62	0.67
EntranceMagnMaindoor	0.19	0.76	0.31	0.41	0.46	0.95	0.63	0.70
BathroomFlushToilet	0.16	0.92	0.27	0.37	0.49	1.00	0.66	0.75
BathroomMagnCabinet	0.07	0.85	0.13	0.18	0.25	0.96	0.40	0.42
BathroomPIRShower	0.49	1.00	0.66	0.37	0.71	1.00	0.83	0.87
BedroomPressureBed	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99
KitchenMagnFridge	0.12	0.84	0.21	0.36	0.40	0.98	0.57	0.67
KitchenMagnCupboard	0.15	0.73	0.24	0.32	0.35	0.89	0.51	0.64
LivingPressureSeat	0.90	0.95	0.92	0.94	0.98	0.94	0.96	0.97
KitchenElectMicrowave	0.37	0.88	0.52	0.66	0.57	0.98	0.72	0.77
KitchenElectToaster	0.63	0.97	0.76	0.86	0.62	0.97	0.76	0.84
Total	0.37	0.89	0.53	0.60	0.56	0.97	0.72	0.77

TABLE 6. Precision P_5, recall R_5 and F1-score F_5 in sensor to sensor translation for RF with a temporal margin of confidence $W = 5$. F_{15} represents the F1-score with $W = 15$.

Sensor	long term FTW				short term FTW			
	P_5	R_5	F_5	F_{15}	P_5	R_5	F_5	F_{15}
BathroomPIRBasin	0.33	0.96	0.49	0.55	0.67	0.97	0.80	0.88
KitchenPIRCooktop	0.84	0.79	0.81	0.86	0.83	0.97	0.90	0.96
EntranceMagnMaindoor	0.89	0.49	0.63	0.65	1.00	0.82	0.90	0.90
BathroomFlushToilet	0.73	0.83	0.77	0.81	0.80	0.85	0.83	0.85
BathroomMagnCabinet	0.73	0.59	0.65	0.75	0.40	0.50	0.45	0.52
BathroomPIRShower	0.99	1.00	0.99	0.99	1.00	1.00	1.00	1.00
BedroomPressureBed	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
KitchenMagnFridge	0.74	0.48	0.58	0.64	0.72	0.58	0.64	0.75
KitchenMagnCupboard	0.91	0.55	0.68	0.70	0.89	0.45	0.60	0.64
LivingPressureSeat	0.95	0.97	0.96	0.97	0.99	0.98	0.99	0.99
KitchenElectMicrowave	0.95	0.77	0.85	0.88	0.71	0.79	0.75	0.89
KitchenElectToaster	0.99	1.00	0.99	1.00	0.99	1.00	0.99	0.99
Total	0.83	0.79	0.81	0.84	0.83	0.82	0.83	0.87

For the best configuration of classifier and FTWs (with Random Forest and short term temporal windows), we have included a deeper evaluation: evaluating the impact of balanced learning and including a activities developed as inputs of domain adaptation.

For that, we present an evaluation of the impact of the size of samples in the learning model adaptation using the clustering method for balancing the activation and non-activation from the daily dataset. In Table, we evaluate the F1-score with next sizes of sample $N = \{150, 400, 800\}$, which shows that computing key patterns of interest and relating them provide an encouraging learning with a low number of samples and the increasing of size of sample is not representative.

TABLE 7. Precision P_5, recall R_5 and F1-score F_5 in sensor to sensor translation for CNN with a temporal margin of confidence $W = 5$. F_{15} represents the F1-score with $W = 15$.

Sensor	long term FTW				short term FTW			
	P_5	R_5	F_5	F_{15}	P_5	R_5	F_5	F_{15}
BathroomPIRBasin	0.33	0.79	0.49	0.55	0.68	0.94	0.79	0.85
KitchenPIRCooktop	0.84	0.79	0.81	0.86	0.86	0.96	0.90	0.98
EntranceMagnMaindoor	0.89	0.49	0.63	0.65	0.70	0.75	0.72	0.73
BathroomFlushToilet	0.73	0.83	0.77	0.81	0.50	0.67	0.58	0.64
BathroomMagnCabinet	0.73	0.59	0.65	0.75	0.16	0.50	0.24	0.27
BathroomPIRShower	0.99	1.00	0.99	0.99	0.98	1.00	0.99	0.99
BedroomPressureBed	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
KitchenMagnFridge	0.74	0.48	0.58	0.64	0.30	0.59	0.40	0.48
KitchenMagnCupboard	0.91	0.55	0.68	0.70	0.99	0.98	0.99	0.99
LivingPressureSeat	0.95	0.97	0.96	0.97	0.60	0.84	0.70	0.76
KitchenElectMicrowave	0.95	0.77	0.85	0.88	0.99	0.96	0.97	0.98
KitchenElectToaster	0.99	1.00	0.99	1.00	0.99	0.96	0.97	0.98
Total	0.63	0.78	0.70	0.77	0.70	0.81	0.75	0.79

TABLE 8. Precision P_5, recall R_5 and F1-score F_5 in sensor to sensor translation for LSTM with a temporal margin of confidence $W = 5$. F_{15} represents the F1-score with $W = 15$.

Sensor	long term FTW				short term FTW			
	P_5	R_5	F_5	F_{15}	P_5	R_5	F_5	F_{15}
BathroomPIRBasin	0.28	0.94	0.43	0.56	0.25	0.95	0.40	0.48
KitchenPIRCooktop	0.92	0.95	0.94	0.98	0.84	0.97	0.90	0.96
EntranceMagnMaindoor	0.74	0.84	0.78	0.83	0.79	0.87	0.83	0.85
BathroomFlushToilet	0.70	0.83	0.76	0.83	0.61	0.87	0.71	0.78
BathroomMagnCabinet	0.16	0.58	0.26	0.29	0.23	0.69	0.34	0.35
BathroomPIRShower	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00
BedroomPressureBed	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
KitchenMagnFridge	0.48	0.63	0.54	0.69	0.66	0.72	0.69	0.79
KitchenMagnCupboard	0.54	0.66	0.59	0.70	0.54	0.66	0.60	0.71
LivingPressureSeat	0.99	0.98	0.99	0.99	0.99	0.98	0.99	0.99
KitchenElectMicrowave	0.71	0.82	0.76	0.83	0.77	0.95	0.85	0.89
KitchenElectToaster	0.90	1.00	0.95	0.99	0.88	1.00	0.94	0.98
Total	0.70	0.85	0.77	0.83	0.71	0.89	0.79	0.84

Next, we have added an evaluation of learning without including our clustering method to compute and relate key patterns of interest between domains. In this case, the samples of time-slots are simply related between the different houses based on the similar temporal progression of the same activity in different domains without clustering and balanced method here proposed. We note how the decreasing of the performance is remarkable and the proposed approach to compute clusters in activities and balanced the learning based on the activation and non-activation is key in obtaining an encouraging performance in domain adaptation of binary sensor from datasets with daily activities. The results are shown in Table 10.

Finally, we present an evaluation where the labeling from activities developed by the inhabitant are included in the feature vector in addition to sensor activation. It should corresponds to including the output from a *perfect* classifier of activity recognition as input sources in the features to increasing the performance in learning. The results are presented in Table 9.

TABLE 9. Precision P_5, recall R_5 and F1-score F_5 in sensor to sensor translation for RF including activity and sensor activation in feature vector with a temporal margin of confidence $W = 5$. F_{15} represents the F1-score with $W = 15$.

Sensor	FTW (Sensor+Actity)			
	P_5	R_5	F_5	F_{15}
BathroomPIRBasin	0.67	0.99	0.80	0.85
KitchenPIRCooktop	0.84	0.98	0.91	0.96
EntranceMagnMaindoor	0.94	0.84	0.89	0.92
BathroomFlushToilet	0.67	0.99	0.79	0.87
BathroomMagnCabinet	0.48	0.81	0.65	0.65
BathroomPIRShower	1.00	1.00	1.00	1.00
BedroomPressureBed	0.99	1.00	0.99	0.99
KitchenMagnFridge	0.62	0.83	0.71	0.85
KitchenMagnCupboard	0.90	0.80	0.84	0.90
LivingPressureSeat	0.99	0.98	0.99	0.99
KitchenElectMicrowave	0.70	0.89	0.79	0.85
KitchenElectToaster	0.95	1.00	0.98	1.00
Total	0.81	0.92	0.87	0.91

TABLE 10. F1-score F_5 margin of confidence $W = \{5, 15\}$ in sensor to sensor translation for datasets with: -cluster) temporal alignment between activities without clustering method to compute and relate key patterns $N = 400$, +cluster+alignment) clustering method to compute and relate key patterns with $N = 400$, $N = 150$ and $N = 800$.

Sensor	-cluster		+cluster+alignment					
Sensor	N=400)		N=150		N=400		N=800	
	F_5	F_{15}	F_5	F_{15}	F_5	F_{15}	F_5	F_{15}
BathroomPIRBasin	0.19	0.27	0.81	0.89	0.80	0.88	0.80	0.89
KitchenPIRCooktop	0.17	0.34	0.86	0.87	0.90	0.96	0.86	0.90
EntranceMagnMaindoor	0.17	0.34	0.86	0.87	0.90	0.90	0.86	0.90
BathroomFlushToilet	0.56	0.64	0.75	0.78	0.83	0.85	0.81	0.84
BathroomMagnCabinet	0.35	0.39	0.47	0.49	0.45	0.52	0.49	0.60
BathroomPIRShower	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
BedroomPressureBed	1.00	0.99	0.99	0.99	1.00	1.00	1.00	1.00
KitchenMagnFridge	0.19	0.32	0.67	0.78	0.64	0.75	0.45	0.53
KitchenMagnCupboard	0.43	0.67	0.64	0.66	0.60	0.64	0.66	0.75
LivingPressureSeat	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
KitchenElectMicrowave	0.31	0.47	0.78	0.80	0.75	0.89	0.87	0.92
KitchenElectToaster	0.87	0.89	1.00	1.00	0.99	0.99	1.00	1.00
Total	0.62	0.70	0.82	0.86	0.83	0.87	0.83	0.87

C. DISCUSSION

From the results provided in the experimental setup, we observe the best configuration in learning the domain adaptation of binary sensors between different environments is RF together with short term temporal features. Despite the fact there is not a relevant difference in performance in case of short and long term features, 0.87 and 0.84 respectively in RF, SVM decreases notably from 0.77 to 0.60. It suggests the short term activation from the source environment is enough for describing the sensor activation in target one, and the inclusion of long term evaluation is not significant in learning process introducing noise in temporal features.

A remarkable result is that the Deep Learning models have shown a slightly lower performance than RF. This fact is related by the capability of RF in handling noisy and uncertain data [50] which are intrinsic in this work from the weak labeling from activity alignment between contexts. The temporal alignment is a weak labeling between domains where not straightforward relation in all instances between domains; so, using a classifier which is robust to noise and imprecision of data, we can obtain encouraging results.

We note, the wide difference of performance in sensor translation is strongly based on the deployment of sensors between contexts. For example, those which are not included in same contexts versus those which are included in same location between contexts. For example the activation of the sensor *BathroomMagneticCabinet* presents the lower result due to the sensor is included only in the input domain, hence the activation prediction of the sensor is difficult using sensor activation from non closer temporal and spatial activations in other context.

The temporal margin to compute the metrics from sensor activations is key to evaluate a sensor to sensor translation because the variances in order and delay of activities in naturalistic conditions are intrinsic to the problem. The temporal margin of 5 minutes $W = 5$ is suitable for most of the sensors, however, a wider temporal margin $W = 15$ improves the metrics sensor from the kitchen where the activities of breakfast and lunch are more complex (they are described by a higher number of relevant clusters).

Then evaluation of the impact of the size of samples in the learning model adaptation, using the clustering method, shows that computing key patterns of interest generate representative samples where learning is not mainly affected by a low number of samples and the increasing of size of sample is not representative. In addition, it is remarkable that we have observed the need for including the clustering approach presented to process datasets with daily activities, which compute clusters and balance the learning based on the activation and non-activation of sensors. The decreasing of performance when only relating the samples based on the temporal progression of activities between domains is notable.

In future works the probability of activation, rather than precision and recall of binary activation or non-activation with a crisp binary value 0, 1, would be an interesting metric for real-life applications. For example, if a given kitchen sensor (microwave) is not *always* activated in lunch (just some times), the translation could generate an activation in the range [0, 1] with an expected value closer to 0.5.

V. CONCLUSION AND ONGOING WORKS

This work presented a domain adaptation method for translating binary sensor activation between different smart environments. This novel approach opens a wide range of possibilities for future works. Domain adaptation was obtained by means of aligning sensor activations by means of human activity developed by source and target domains without the need to establish additional labeling to relate the sensor activation. An evaluation procedure was necessary to evaluate the data in a quantitative way, so, in order to validate the adaptation model, in this work, we presented an evaluation method based on cross validation and inverse translation, which we have validated using an openly available dataset. For learning the activation for each sensor in the target domain an ad-hoc dataset and classifier are proposed.

The results highlighted promising performance in the convoluted problem of sensors translation between different contexts. Random Forest is an alternative more robust to noise, an essential requirement when learning from a weak labeling like the one provided by temporal alignment of activities between both contexts.

The adversarial networks could develop promising results based on previous performance within domain adaptation [51]; however, visual models would require an adaptation to temporal sequence to sequence learning of sensors and including balancing and computing of key patterns of interest which have been described in this work. Additionally, the development of AR, in order to include the prediction of activities as input from domain, in a parallel way to domain adaptation is consider as an appropriate ongoing work.

Regarding the proposed evaluation method, the error in sensor to sensor translation was calculated after a double translation process. Alternative procedures may be considered in future work, avoiding the need for double translation. For instance, a knowledge-based approach could validate the sensor to sensor translation between domains checking the statistical differences between real and estimated data. In addition, we note that it is necessary to collect new labeled datasets with an extensive data collection in the context of real-life homes to enable the domain adaptation between different multi-domain contexts.

APPENDIX

REPRESENTATION OF BINARY SENSORS WITH FUZZY TEMPORAL WINDOW BY TRAPEZOIDAL MEMBERSHIP FUNCTIONS

The FTWs are described straightforwardly according to the distance from the current time t^* to a given timestamp t^j as $\Delta t^j = t^* - t^j$ using the membership function $\mu_{T_K(\Delta t^j)}$. Each TFW T_k is described by a trapezoidal function based on the time interval from a previous time t^j to the current time t^*: $T_k(\Delta t^j)[l_1, l_2, l_3, l_4]$ and a fuzzy set characterized by a membership function whose shape corresponds to a trapezoidal function. The well-known trapezoidal membership functions are defined by a lower limit l_1, an upper limit l_4, a lower support limit l_2, and an upper support limit l_3 (refer to Equation (4)):

$$TS(x)[l_1, l_2, l_3, l_4] = \begin{cases} 0 & x \leq l_1 \\ (x-l_1)/(l_2-l_1) & l_1 < x < l_2 \\ 1 & l_2 \leq x \leq l_3 \\ (l_4-x)/(l_4-l_3) & l_3 < x < l_4 \\ 0 & l_4 \leq x \end{cases} \quad (4)$$

Therefore, a given FTW T_k is defined by the values $L_k, L_{k-1}, L_{k-2}, L_{k-3}$, which determine a trapezoidal membership function as:

$$T_k = T_k(\Delta t_i^*)[L_k, L_{k-1}, L_{k-2}, L_{k-3}] \quad (5)$$

Once a FTW T_k is defined, the activation degree of a binary activation S_{i_j} from a sensor S_i at evaluated time t^* is computed as:

$$T_k(S_{i_j}, t^*) = \begin{cases} max(T_k(\Delta t_i^*)) \forall t_i \in S_{i_j} & \exists t_i \in [S_{i_j}^0, S_{i_j}^+] \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

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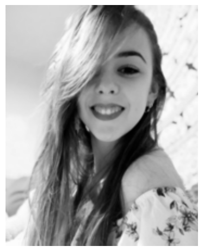

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